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Terrain-Based Navigation of Planetary Rovers: A Fuzzy Logic Approach

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Abstract

This paper presents a new strategy for autonomous navigation of field mobile robots on hazardous natural terrain using a fuzzy logic approach and a novel measure of terrain traversability. The navigation strategy is comprised of three simple, independent behaviors: seek-goal, traverse-terrain, and avoid-obstacle. The recommendations from these three behaviors are combined through appropriate weighting factors to generate the final steering and speed commands that are executed by the robot. The weighting factors are produced by fuzzy logic rules that take into account the current status of the robot. This navigation strategy requires no a priori information about the environment, and uses the on-board traversability analysis to enable the robot to select relatively easy-to-traverse paths autonomously. Field test results obtained from implementation of the proposed algorithms on the commercial Pioneer AT rover are presented. These results demonstrate the real-time capabilities of the terrain assessment and fuzzy logic navigation algorithms.

1 Introduction

In recent years, there has been a growing interest in navigation of field mobile robots that operate on outdoor natural terrain. There are several application domains, both terrestrial and in space, which have strongly motivated this research. For instance, NASA has planned an ambitious set of missions to Mars that will carry mobile robots (rovers) to explore the Martian surface and to carry out in-situ science tasks. After the success of the Sojourner rover in 1997, there has been a strong motivation to develop future planetary rovers with enhanced capabilities that can explore remote planets autonomously and intelligently with minimal human intervention. Similarly, DARPA is sponsoring several research projects that involve autonomous mobile robots operating on natural terrain.

Despite widespread applications of outdoor navigation, there are only a few existing methods for field robot navigation that consider the terrain characteristics. In the current methods [1-8], terrain traversability is defined as an analytical function of the terrain slope and roughness. The slope is determined by finding the least-squares fit of a geometric plane covering the region, while the roughness is calculated as the residual of the best plane fit. Once the traversability of each region is found, a traversable path for the robot to follow is then constructed. These analytical representations of the terrain traversability rely on accurate interpretation of the sensory data, as well as a precise mathematical definition of the traversability function.

This paper develops a new strategy for autonomous navigation of field mobile robots using a novel representation of the terrain quality. The premise of the proposed approach is to embed the human expert's heuristic knowledge into the mobile robot navigation strategy using fuzzy logic tools. The robot navigation strategy developed here is comprised of three simple, independent behaviors: seek-goal, traverse-terrain, and avoid-obstacle. The recommendations from these behaviors are combined with appropriate weighting factors to yield an autonomous navigation strategy for the mobile robot that requires no *a priori* information about the environment.

The paper is organized as follows. The robot navigation behaviors based on goal, terrain, and obstacle information are presented in Sections 2-4. The combination of these behaviors into a unified robot navigation strategy is discussed in Section 5. Field test studies are reported in Section 6. Finally, Section 7 draws conclusions from this work.

2 Seek-Goal Behavior

The problem addressed in this section is to navigate a mobile robot on a natural terrain from a known initial position to a user-specified goal position. The control variables of the robot are the translational speed v and the rotational speed (or turn rate) ω, where $v = \sqrt{(\frac{dx}{dt})^2 + (\frac{dy}{dt})^2}$, $\omega = \frac{d\theta}{dt}$, and x, y, and θ are the position coordinates of the robot center and the robot orientation, respectively. The robot speed v is represented by the four linguistic fuzzy sets {STOP, SLOW, MODERATE, FAST}, with the membership functions shown in Figure 1a. Similarly, the robot turn rate ω is represented by the five linguistic fuzzy sets {FAST-LEFT, SLOW-LEFT, ON-COURSE, SLOW-RIGHT, FAST-RIGHT}, with the membership functions shown in Figure 1b. We shall now present fuzzy navigation rules for the seek-goal behavior.

The fuzzy rules for the robot rotational motion are as follows:

- IF ϕ is FAR-LEFT, THEN ω is FAST-LEFT.
- IF ϕ is NEAR-LEFT, THEN ω is SLOW-LEFT.
- IF ϕ is HEAD-ON, THEN ω is ON-COURSE.
- IF ϕ is NEAR-RIGHT, THEN ω is SLOW-RIGHT.
- IF ϕ is FAR-RIGHT, THEN ω is FAST-RIGHT.

where the heading error ϕ is represented by the five linguistic fuzzy sets {FAR-LEFT, NEAR-LEFT, HEAD-ON, NEAR-RIGHT, FAR-RIGHT}.

The following rules are used for the robot translational motion:

- IF d is VERY-NEAR OR ϕ is NOT HEAD-ON, THEN v is STOP.
- IF d is NEAR AND ϕ is HEAD-ON, THEN v is SLOW.
- IF d is FAR AND ϕ is HEAD-ON, THEN v is MODERATE.
- IF d is VERY-FAR AND ϕ is HEAD-ON, THEN v is FAST.

where the position error (goal distance) d is represented by the four linguistic fuzzy sets {VERY-NEAR, NEAR, FAR, VERY-FAR}.

3 Traverse-Terrain Behavior

This section is comprised of two parts. In the first part, new techniques are developed for real-time terrain assessment by inferring physical properties of the terrain (such as roughness and slope) from the data provided by on-board cameras. In the second part, novel techniques for terrain-based navigation are developed in which the terrain quality data are used directly in the robot navigation logic so as to guide the robot toward the most traversable terrain.

3.1 Real-Time Terrain Assessment

In recent papers [9-10], the concept of *rule-based* Fuzzy Traversability Index is introduced as a simple measure for quantifying the suitability of a natural terrain for traversal by a mobile robot. Two important attributes that characterize the difficulty of a terrain for traversal are the slope and roughness of the region. The Fuzzy Traversability Index can thus be defined in terms of these two physical parameters using a rule-based approach [1]. These terrain parameters are computed from video image data obtained by the stereo cameras mounted on the mobile robot.

3.1.1 Terrain Roughness

A new approach is developed in this section to quantify the roughness of a region. First, an algorithm for determining the size and concentration of rocks in a viewable scene is applied to a pair of stereo camera images. A horizon-line extraction program is run that identifies the peripheral boundary of the ground

[1] The Fuzzy Traversability Index also depends on the wheel design and traction mechanism of the robot which determine its hill climbing and rock climbing capabilities.

plane. This, in effect, recognizes the line at which the ground and the landscaped backdrop intersect. The algorithm then identifies target objects located on the ground plane using a region-growing method [11]. In effect, targets that differ from the ground surface are identified and counted as rocks for inclusion in the roughness assessment. To determine the number of small and large-sized rocks contained within the image, the number of pixels which comprise a target object are first counted. Those targets with a pixel count less than a user-defined threshold are labeled as belonging to the class of small rocks and those with a count above the threshold are classified as large rocks. This defines the {SMALL, LARGE} fuzzy sets that represent the rock sizes. All such labeled target objects are then grouped according to their sizes in order to determine the small and large rock concentration parameters. This value is characterized by the linguistic fuzzy sets {FEW, MANY}. The terrain roughness β is represented by the three linguistic fuzzy sets {SMOOTH, ROUGH, ROCKY}, with the trapezoidal membership functions shown in Figure 2a. The terrain roughness is derived directly from the rock size and concentration parameters of the associated image scene using the fuzzy logic rules summarized in Table 1. Observe that this rule-based approach gives a perceptual, linguistic definition of terrain roughness as used by a human observer, in contrast to a mathematical definition of roughness (as the residual of the least-squares plane fit) used previously [1-6].

3.1.2 Terrain Slope

To obtain the terrain slope from a pair of stereo camera images, we must first calculate the real-world Cartesian x, y, z components of the ground plane boundary. We can determine the average slope value α using the equation $\alpha = \frac{1}{N}\sum_i^N atan2(z_i, x_i)$, where N is the number of horizon-line points viewable in both images. To determine the x, y, z components of the horizon-line, Tsai's camera calibration model [12] is used to derive the relationship between the camera image and the real-world object position for a single camera. The images from both cameras are then matched in order to retrieve 3D information. Given a pair of stereo camera images, correlated image points that lie along the horizon-line are first extracted from each camera image. Determining the position of the largest rocks located along the horizon-line and centered within both images allows the identification of correlated image points. These image points are then used as input for extraction of the (x, y, z) real-world Cartesian components. Once all Cartesian points are calculated, they are used for slope determination. The terrain slope α is represented by the three linguistic fuzzy sets {FLAT, SLOPED, STEEP}, with the trapezoidal membership functions shown in Figure 2b.

3.1.3 Terrain Traversability

The Fuzzy Traversability Index τ is represented by the three linguistic fuzzy sets {LOW, MEDIUM, HIGH}, with the trapezoidal membership functions shown in Figure 2c. The Fuzzy Traversability Index τ is defined in terms of the terrain slope α and the terrain roughness β by a set of simple fuzzy logic rules summarized in Table 2. Again, observe that this rule-based approach lends itself to a perceptual, linguistic definition of terrain traversability as used by a human observer, in contrast to a mathematical definition of traversability (as an analytical function of slope and roughness) used previously [1-6].

3.2 Terrain-Based Navigation

The terrain in front of the robot is partitioned into three 60° sectors, namely: front, right, and left of the robot[2] at a distance of up to about 10 meters. The Traversability Indices for the above three regions, τ_f, τ_r, τ_l, are computed from the measurements of the terrain slope and roughness obtained by the vision system on-board the robot. We shall now discuss the fuzzy rules for determination of the robot turn rate and speed based on the terrain traversability data.

The terrain-based turn rules are summarized in Table 3. Observe that a turn maneuver is not initiated when either the front region is the most traversable, or the right and left regions have the same traversability indices as the front region. Note that the "preferred" direction of turn is chosen arbitrarily to be LEFT, i.e., when the robot needs to turn to face a more traversable region, it tends to turn left.

[2] Note that if higher resolution is needed, the 180° field-of-view can be decomposed into a larger number of smaller sectors and similar navigation rules can be developed.

Once the direction of traverse is chosen based on the relative values of τ, the robot speed v can be determined based on the value τ^* of the Traversability Index τ in the *chosen region*. This determination is formulated as a set of two simple fuzzy logic rules for speed of traverse as follows:

- IF τ^* is LOW, THEN v is STOP.
- IF τ^* is MEDIUM, THEN v is SLOW.

4 Avoid-Obstacle Behavior

It is assumed that there are three groups of proximity sensors mounted on the robot facing the three different directions of front, right, and left. These sensors report the distances between the robot and the closest front obstacle d_f, the closest right obstacle d_r, and the closest left obstacle d_l within their ranges of operation. Each obstacle distance is represented by the three linguistic fuzzy sets {VERY-NEAR, NEAR, FAR}. The fuzzy logic turn rules are similar to Table 3. There are two fuzzy logic move rules as follows:

- IF d_f is VERY-NEAR, THEN v is STOP.
- IF d_f is NEAR, THEN v is SLOW.

Again, note that when the front obstacle distance is FAR, collision avoidance is not activated and no corrective action needs to be taken.

5 Combination of Multiple Behaviors

The process of combining recommendations from multiple behaviors has been a topic of active research in recent years [see 13 for an overview]. The most common approach is behavior arbitration wherein the recommendation of only one behavior is taken and others are ignored. In this section, we develop a different approach by allowing multiple behaviors to affect the final control action. Once the three behaviors have made independent recommendations for the robot motion, their recommendations are combined through variable gains or weighting factors that are determined based on consideration of the current status of the robot. The weighting factors s^w, t^w, and a^w represent the strengths by which the seek-goal, traverse-terrain, and avoid-obstacle recommendations are taken into account to compute the final control actions $\bar{v}$ and $\bar{\omega}$. These weights are represented by the two linguistic fuzzy sets {NOMINAL, HIGH}. Three sets of weight rules for the three behaviors are now presented.
The seek-goal weight rules are as follows:

- IF d is VERY-NEAR, THEN s^w is HIGH.
- IF d is NOT VERY-NEAR, THEN s^w is NOMINAL.

The traverse-terrain weight rules are as follows:

- IF d is NOT VERY-NEAR AND d_f is NOT VERY-NEAR, THEN t^w is HIGH.
- IF d is VERY-NEAR OR d_f is VERY-NEAR, THEN t^w is NOMINAL.

Finally, the avoid-obstacle weight rules are as follows:

- IF d is NOT VERY-NEAR, THEN a^w is HIGH.
- IF d is VERY-NEAR, THEN a^w is NOMINAL.

At each control cycle, the above sets of weight rules are used to calculate the three crisp weighting factors using the Center-of-Gravity (Centroid) defuzzification method [14]. The resulting crisp weights are then used to compute the final control actions for the robot speed and turn rate using the Centroid method.

6 Field Test Studies

Field tests using the Pioneer All-Terrain (AT) rover are conducted on rough terrain outside JPL to test the reasoning and decision-making capabilities provided by the fuzzy logic navigation strategy. Five front-facing and two side-facing sonars are located in the rover base for obstacle detection up to 2 meters away. The rover is able to determine its current location relative to a given starting position using its internal wheel-encoder information. The Pioneer rover is augmented with additional on-board processing capability, 8-input image multiplexer, and six CMOS NTSC video cameras. The processing power on-board the rover consists of a 333 MHz Pentium II processor housed in a chassis mounted at the rear of the rover that runs under the Linux operating system. An alternative on-board computing platform is a laptop computer running under the Windows 95 operating system. In both configurations, resident on the on-board computer is the image processing algorithms and the fuzzy logic computation engine used to calculate the translational and rotational speed commands issued to control the wheel motors. Using this hardware platform, rover field tests are performed outdoors in natural terrain. Two sets of field tests are conducted to test the navigational capabilities of the rover.

6.1 Field Test One

In the first field test, the three navigation behaviors, seek-goal, traverse-terrain, and avoid-obstacle, are utilized by the rover to navigate from a starting position to a user-specified goal position. The goal position is located approximately 20 meters in front of the rover. Directly in-between the starting and the goal positions are two regions having low traversability - one region contains a highly sloped hill and the other contains a large cluster of rocks. The on-board system first begins by analyzing the traversability of the three partitioned 60° sectors (left, front, right) of the terrain located in front of the rover. The front and left sectors (which contain the large sloped hill) are found to have low traversability. The rover therefore turns toward the right sector which is found to be highly traversable and proceeds to enter the safe region. Once in the safe region, the rover turns and navigates toward the goal, while ensuring that it is still physically located in the highly traversable sector. After traversing a distance of about 10 meters from start, the rover stops, turns toward the goal, and re-analyzes the traversability of the terrain ahead of it. This time the front sector is found to have low traversability due to the large cluster of rocks located in this area. The left region is found to have low traversability due to the large sloped hill, and the right region is once again found to have high traversability. The rover thus turns to the right and proceeds into the safe region. At the point when the rover is within 1.5 meters of the goal, the weight on the traverse-terrain recommendation is reduced automatically, and the seek-goal behavior becomes dominant. At this point, the rover heads directly toward the goal. Figure 3 shows the path traversed by the rover from its original starting position until it autonomously reaches the specified goal position using its on-board fuzzy logic navigation rules.

6.2 Field Test Two

In the second set of field tests, the influence of the newly-introduced traverse-terrain behavior on the navigation logic is demonstrated. In this test, the goal position is located approximately 10 meters in front of the rover. In addition, a large cluster of rocks is located directly between the rover starting position and the specified goal position. For the first test, the rover is commanded to navigate to the specified goal position while the traverse-terrain behavior is disabled, i.e. the recommendations from the traverse-terrain behavior are totally ignored by pre-setting the traverse weight to zero. As the rover navigates toward the goal, it enters into the cluster of rocks. At this point, the rover slows down and creeps its way into the center of the cluster. Eventually, the rover halts when its sonars identify rock obstacles located on all three sides (front, left, right). As shown in Figure 4a, the rover easily gets trapped in the cluster of rocks. For the second test, the traverse-terrain behavior is enabled and the rover is shown to successfully reach the goal position (Figure 4b). In this test, the front sector is found to have low traversability and thus the traverse-terrain behavior commands the rover to circumnavigate the cluster of rocks. This test demonstrates that the traverse-terrain behavior can effectively analyze and incorporate the terrain information directly into the navigation logic and ensure successful attainment of the goal position by preventing entry and entrapment in the rock cluster.

7 Conclusions

Rule-based robot navigation strategies using fuzzy logic have major advantages over analytical methods. First, the fuzzy rules that govern the robot motion are easily understandable, intuitive, and emulate the human driver's experience. Second, the tolerance of fuzzy logic to imprecision and uncertainty in sensory data is particularly appealing for outdoor navigation because of the inevitable inaccuracy in measuring and interpreting the terrain quality data, such as slope and roughness. And third, the fuzzy logic strategy has a modular structure that can be extended very easily to incorporate new behaviors – whereas this requires complete reformulation for analytical methods. Multiple fuzzy navigation behaviors can be combined into a unified strategy, together with smooth interpolation between the behaviors to avoid abrupt and discontinuous transitions.

The addition of the on-board terrain sensing and traversability analysis, coupled with the traverse-terrain behavior that takes advantage of this information, are significant and novel contributions of this paper. These capabilities allow the navigation system to take preventive measures by "looking ahead" and preventing the robot from entry and entrapment in rock clusters and other impassable regions, and instead guiding the robot to circumnavigate these regions.

8 Acknowledgment

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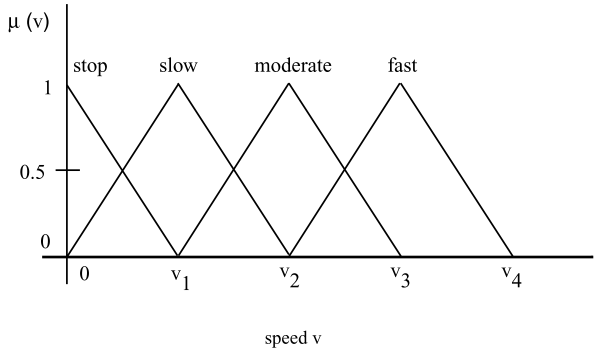

Figure 1a. Membership functions for speed

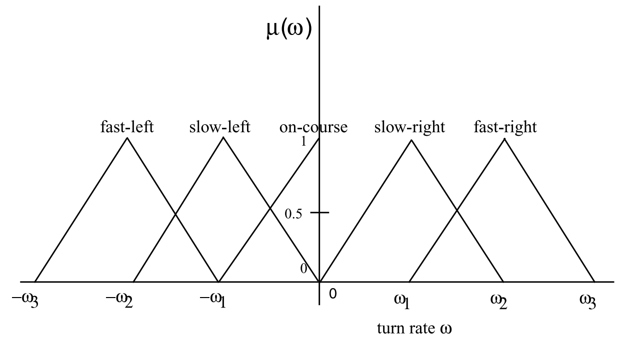

Figure 1b. Membership functions for turn rate

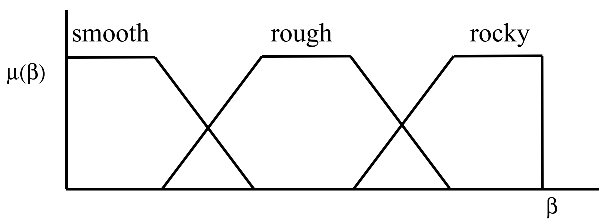

Figure 2a. Membership functions for terrain roughness

ROCK CONCENTRATION \ ROCK SIZE	SMALL	LARGE
FEW	SMOOTH	ROUGH
MANY	ROUGH	ROCKY

Table 1. Fuzzy rules for terrain roughness

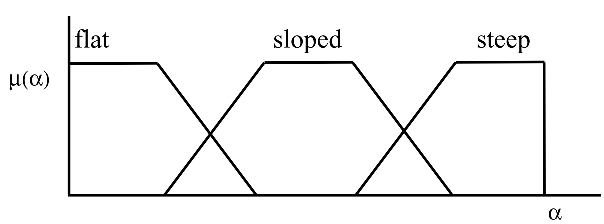

Figure 2b. Membership functions for terrain slope

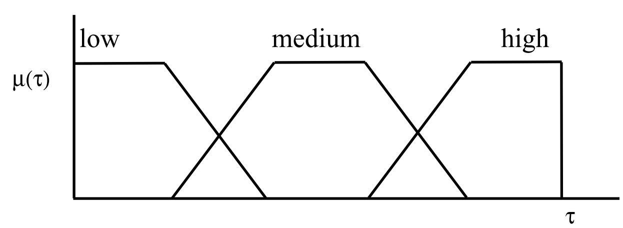

Figure 2c. Membership functions for traversability index

ROUGHNESS \ SLOPE	FLAT	SLOPED	STEEP
SMOOTH	HIGH	MED	LOW
ROUGH	MED	LOW	LOW
ROCKY	LOW	LOW	LOW

Table 2. Fuzzy rules for traversability index

τ_f low

τ_l \ τ_r	high	medium	low
high	L	L	L
medium	R	L	L
low	R	R	O

τ_f medium

τ_l \ τ_r	high	medium	low
high	L	L	L
medium	R	O	O
low	R	O	O

τ_f high

τ_l \ τ_r	high	medium	low
high	O	O	O
medium	O	O	O
low	O	O	O

Table 3. Turn rules for the traverse-terrain behavior

Figure 3. Navigation path using fuzzy logic navigation rules. Top-left image shows rover's initial starting position and bottom image indicates goal achievement. Image sequence proceeds from left to right and top to bottom.

Figure 4a. Entrapment without traverse-terrain behavior

Figure 4b. Circumnavigation with traverse-terrain behavior